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Fairness and QoS Comparison of Equal, Max-Min, and Demand-Proportional Allocation in 5G Network Slicing

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Abstract: 5G network slicing allows services with very different requirements to share one physical infrastructure, and an equal split of capacity is often reported as the fairest outcome because it maximises Jain's fairness index. An index computed on raw allocations, however, says nothing about whether heterogeneous slices receive what they actually need. This study therefore compares three allocation policies, Equal Allocation, Max-Min Fairness and Demand-Proportional Allocation, for four slices representing enhanced mobile broadband, ultra-reliable low-latency, machine-type and best-effort traffic. The slices share 100 MHz of bandwidth and 100 computing units. Every replication generates one Poisson demand realisation that is supplied unchanged to all three policies, and 100 replications are executed at low, medium and high load. Fairness is measured both on the raw allocation and on demand satisfaction, and is reported together with served bandwidth, utilisation, analytical delay, jitter and loss proxies, and service level agreement satisfaction. Because the design is paired, the Friedman test and Holm-corrected Wilcoxon signed-rank tests are applied. Equal Allocation reaches an allocation fairness index of 1.000 at every load, yet its satisfaction fairness falls to 0.866 and it satisfies only 54.2% of slices at high load. Demand-Proportional Allocation equalises satisfaction perfectly (1.000) but satisfies 12.0%, whereas Max-Min Fairness satisfies 62.5%. Resource equality, satisfaction fairness and service fairness therefore rank the same three policies differently, so slicing studies should report all three perspectives.

Keywords: 5G network slicing; demand satisfaction; Jain's fairness index; max-min fairness; service level agreement

INTRODUCTION

Network slicing partitions one fifth-generation infrastructure into logical networks that serve different classes of traffic. Enhanced mobile broadband needs high data rates, ultra-reliable low-latency communications needs short and predictable response times, massive machine-type communications aggregates many small transfers, and best-effort traffic absorbs whatever capacity remains. All of these slices draw on the same pool of radio and computing resources, so the rule that divides that pool decides both how efficiently the infrastructure is used and how well each tenant is served (Su et al., 2019; Huang et al., 2021; Ko et al., 2021).

Fairness is the property most often invoked when such a rule is justified, and it is usually quantified with the index of Jain et al. (1984), sometimes together with the Gini coefficient. Both measures are computed on the vector of allocated quantities, so an equal split reaches the best possible score by construction. That result is a property of the measurement, not evidence that the outcome serves the tenants well: a slice that requested little and a slice that requested a great deal are treated as equally satisfied when they receive the same quantity. The axiomatic literature makes the same point in general terms, showing that a fairness measure only becomes meaningful once the quantity being equalised has been chosen deliberately (Lan et al., 2010).

The problem addressed in this paper is that the three classical policies used in slicing studies are rarely compared under conditions that isolate the effect of the rule itself, and that their fairness is rarely reported from more than one perspective. Published comparisons often draw fresh random traffic for each policy, which mixes the effect of the allocation rule with the effect of the demand sample, and they often stop at the fairness of the raw allocation. Recent measurements on sliced testbeds confirm that identical resource assignments can translate into very different application-level outcomes (Moreira et al., 2024), which makes the distinction between resource fairness and service fairness a practical concern rather than a semantic one.

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The objective of this study is therefore to compare Equal Allocation, Max-Min Fairness and Demand-Proportional Allocation under identical stochastic demand, and to report the outcome from three perspectives: equality of the allocated resources, fairness of demand satisfaction, and satisfaction of a service level agreement. The paper does not propose a new allocation algorithm. It is deliberately positioned as a controlled and reproducible benchmarking study, and its contribution lies in the experimental design and in the evaluation. The same demand realisation is supplied to every policy in every replication, so the comparison is paired and the statistical analysis uses tests appropriate for repeated measures. Fairness is evaluated on raw allocations and on allocation-to-demand ratios, bandwidth and computing resources are allocated jointly, and the analytical nature of the delay, jitter and loss proxies is stated explicitly instead of being presented as packet-level measurement. The three policies are further shown to be three instances of one weighted proportional-fair program, which clarifies what the implemented proportional rule does and does not solve (Kelly et al., 1998). Finally, a sensitivity analysis varies the shared capacity and the service threshold to show how far the ranking of the policies depends on the chosen operating point.

LITERATURE REVIEW

Resource allocation for network slicing has been surveyed as a combination of resource modelling, optimisation, isolation and quality-of-service enforcement (Su et al., 2019), and machine learning has since become a common tool for radio access network slicing (Azimi et al., 2022). Reinforcement learning has been applied to constrained allocation (Liu et al., 2021), to admission control combined with allocation (Chakraborty & Sivalingam, 2023), to two-tier allocation with joint bidding (Chen, Zhang, et al., 2022), and to allocation driven by traffic prediction (Chen, Mu, et al., 2022). Optimisation-based formulations include equilibrium-constrained programs for heterogeneous radio access networks (Ma et al., 2022), cooperative-aware allocation in cloud radio access networks (AlQahtani, 2023), joint quality-of-service and energy-efficient scheduling (Saibharath et al., 2023), Lyapunov optimisation with delay guarantees (Chai & Wang, 2025), and model predictive control for resilient slicing (Fryganiotis et al., 2025). These studies pursue new mechanisms; the baselines against which they are measured are usually the classical fairness policies examined here.

Fairness itself has been treated from several angles. The index of Jain et al. (1984) measures equality of an allocation vector, whereas the axiomatic theory of fairness relates fairness criteria to families of utility functions (Lan et al., 2010). Proportional fairness is defined through logarithmic utility maximisation and the associated shadow prices (Kelly et al., 1998), and it is still applied in recent slicing work, for example to joint allocation and slicing in hybrid radio and visible-light systems (Rajahrajasingh et al., 2026). Max-min planning has been revisited for energy-efficient software-defined 5G networks (Jiang et al., 2024), and bandwidth fairness has been implemented directly in switches (MacDavid et al., 2024) and in programmable data planes (Ran et al., 2024). Equitable sharing between tenants with priority-based isolation (Yarkina et al., 2022), knowledge-based flexible allocation (Kumar & Ahmad, 2023), market-based allocation (Datar et al., 2023) and fairness-aware cache allocation based on bankruptcy games (Bamdad et al., 2026) all extend fairness beyond the equal division of a single resource.

A third group of studies evaluates allocation against service commitments rather than against equality. Deep reinforcement learning has been used to guarantee service level agreements in heterogeneous networks (Zhang et al., 2022), hierarchical slicing has been designed for differential service level agreements (Li et al., 2024), and hybrid non-orthogonal access has been optimised for the coexistence of broadband and low-latency services (Chandra Sekhar & Singh, 2024). Measurements on sliced testbeds show that the mapping from allocated resources to application performance is not uniform across slices (Moreira et al., 2024).

Two gaps follow from this literature. First, the classical policies are used as baselines far more often than they are characterised, and comparisons rarely guarantee that competing policies faced exactly the same demand. Second, fairness is usually reported on raw allocations even though service commitments are expressed in terms of satisfied demand. The present study addresses both gaps for the three policies of interest, without proposing a new mechanism.

METHOD

System Model and Traffic Generation

The modelled infrastructure hosts four slices, denoted eMBB, URLLC, mMTC and Best Effort, that share 100 MHz of bandwidth and 100 processing units. For each slice the number of active users is drawn uniformly from 20 to 100, and each user issues a Poisson-distributed number of requests whose rate depends on the load level. Best Effort traffic is scaled by a multiplier of 0.5 to represent lighter background activity. Bandwidth and computing demand follow from the request count and the per-request resource unit of the service class, as given in (1), where N denotes the number of generated requests and u the per-request unit. Table 1 lists the four service profiles.

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$$D_{i,BW} = N_{i,req}\, u_{i,BW}, \quad D_{i,CPU} = N_{i,req}\, u_{i,CPU} \tag{1}$$

Table 1. Service profiles and per-request resource units.

Slice	Service type	Bandwidth per request (MHz)	CPU per request (units)	Traffic multiplier
eMBB	Enhanced mobile broadband	0.10	0.04	1.0
URLLC	Ultra-reliable low-latency	0.05	0.08	1.0
mMTC	Massive machine-type	0.02	0.03	1.0
Best Effort	Background traffic	0.04	0.02	0.5

An allocation assigns a non-negative quantity to every slice and cannot exceed the shared capacity, as stated in (2). The same rule is applied independently to the bandwidth pool and to the computing pool, so both resources are allocated jointly within one replication.

$$x_i \geq 0, \quad \Sigma_i x_i \leq C, \quad i = 1, \ldots, n, \quad n = 4 \tag{2}$$

Allocation Policies and Their Proportional-Fair Formulation

Equal Allocation divides the shared capacity evenly, as in (3), and ignores demand entirely. It represents pure equality of resources. It is deliberately not called a Jain-based policy: Jain's index is an evaluation metric applied to the output of every policy, not an allocation algorithm.

$$x_i = C / n \tag{3}$$

Max-Min Fairness is computed by progressive filling. The capacity is raised uniformly for all slices that are still unsatisfied; a slice that reaches its demand leaves the active set and its surplus is redistributed. The resulting allocation is the water-filling solution in (4), where the level is chosen so that the whole available capacity, or the whole demand, is used.

$$x_i = \min(d_i, \theta), \quad \Sigma_i \min(d_i, \theta) = \min(C, \Sigma_i d_i) \tag{4}$$

Demand-Proportional Allocation grants every slice its full demand when the total demand fits inside the capacity, and otherwise shares the scarce capacity in direct proportion to demand, as in (5). The policy is named after what the implementation does. It is not presented as a general proportional-fair scheduler, because it does not maximise the unweighted logarithmic utility and does not track the ratio of an achievable rate to a historical average rate.

$$x_i = d_i \text{ if } \Sigma_j d_j \leq C, \quad \text{otherwise } x_i = C\, d_i / \Sigma_j d_j \tag{5}$$

The relationship to proportional fairness can nevertheless be stated exactly. Proportional fairness is defined as the maximisation of a logarithmic utility subject to the capacity constraint (Kelly et al., 1998), and its weighted form admits per-slice weights and per-slice upper bounds, as written in (6). An allocation solves (6) if and only if the variational condition in (7) holds for every feasible allocation y, which is the standard characterisation of a proportional-fair point.

$$\text{maximise } \Sigma_i w_i \log x_i \quad \text{subject to } \Sigma_i x_i \leq C, \quad 0 \leq x_i \leq u_i \tag{6}$$

$$\Sigma_i w_i (y_i - x_i) / x_i \leq 0 \tag{7}$$

The three policies of this study are the three instances of (6) that are obtained by choosing the weights and the upper bounds. Equal Allocation corresponds to unit weights without demand bounds, Max-Min Fairness to unit weights with the demand as upper bound, and Demand-Proportional Allocation to weights equal to the demands with the demand as upper bound. The implemented rule is therefore the weighted proportional-fair allocation whose weights are the slice demands, and it coincides with unweighted proportional fairness only when all demands are equal. Algorithm 1 states the three rules and the stopping criterion of the progressive-filling loop.

Algorithm 1. The three allocation policies of the original study.

```
Input : demand vector d, shared capacity C, slice count n
Output: allocation vector x with sum(x) <= C
Equal Allocation
   for i = 1..n: x[i] <- C / n
Max-Min Fairness (progressive filling)
   x <- 0 ; R <- C ; A <- {1..n}
   while A is not empty and R > eps:
      share <- R / |A|
      for i in A with d[i] - x[i] <= share: x[i] <- d[i] ;
         R <- R - (d[i] - x[i]) ; remove i from A
      if no slice was removed in this pass:
         for i in A: x[i] <- x[i] + share ; R <- 0
   stop when A is empty (all demands met) or R = 0
Demand-Proportional Allocation
```


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```
if sum(d) <= C: x <- d
else: for i = 1..n: x[i] <- C * d[i] / sum(d)
```

The equivalence was verified numerically rather than only asserted. For each of the 300 demand realisations of the experiment, the program in (6) was solved with a constrained numerical optimiser and the solution was compared with the output of the implemented policy, and the condition in (7) was tested against random feasible allocations. The largest deviation between the closed-form policy and the optimiser was 1.2e-06 MHz, and the largest violation of (7) was 3.9e-14, both at the level of numerical tolerance. A worked example illustrates the difference between the policies. In one high-load replication the bandwidth demands are 65.40, 54.40, 12.02 and 18.32 MHz, a total of 150.14 MHz against a capacity of 100 MHz. Equal Allocation gives 25.00 MHz to every slice, Max-Min Fairness gives 34.83, 34.83, 12.02, 18.32 MHz, and Demand-Proportional Allocation gives 43.56, 36.23, 8.01, 12.20 MHz. Max-Min Fairness fully serves the two small slices and splits the remainder evenly, whereas Demand-Proportional Allocation keeps every slice at the same fraction of its demand.

Fairness Measures

Three fairness perspectives are reported, because they answer different questions. Equality of resources asks whether the slices received the same quantity and is measured by Jain's index in (8) and by the Gini coefficient in (9), both applied to the allocation vector. Demand-aware fairness asks whether the slices received the same fraction of what they asked for; the satisfaction of a slice is defined in (10), and the same two measures are then applied to the satisfaction vector. Service fairness asks how many slices actually met their commitment, and is measured by the share of slices whose satisfaction reaches the 0.90 threshold of the service level agreement. The minimum satisfaction across slices is reported as well, because it identifies the worst-served slice.

$$J(x) = (\Sigma_i x_i)^2 / (n \Sigma_i x_i^2) \quad (8)$$

$$G(x) = \Sigma_i \Sigma_j |x_i - x_j| / (2 n \Sigma_i x_i) \quad (9)$$

$$s_i = min(x_i, d_i) / d_i \quad (10)$$

Quality-of-Service Proxies

The simulator works at the level of resource quantities. It does not generate individual packets, does not model a queue or a buffer, and does not simulate a radio protocol stack. Delay, jitter and loss are therefore analytical proxies derived from the ratio between demand and allocation, and they are reported as such. The offered-load ratio of a slice is defined in (11) and is capped so that a starved slice cannot produce an unbounded value. Delay grows linearly with that ratio from a base value of 10 ms, as in (12), while jitter grows quadratically, as in (13), which reflects the faster deterioration of delay variation near saturation. Both quantities are averaged over the slices with weights proportional to demand. The loss proxy in (14) is the share of the total demand that cannot be served. Served bandwidth is the sum of the served quantities and is used as a resource-level throughput proxy; bandwidth and computing utilisation are the served quantities divided by the corresponding capacity. No claim of packet-level measurement is made anywhere in this paper.

$$\rho_i = min(d_i / x_i, \rho_{max}), \quad \rho_{max} = 10 \quad (11)$$

$$T = \Sigma_i d_i \cdot 10\rho_i / \Sigma_i d_i \quad (12)$$

$$V = \Sigma_i d_i \cdot 0.4 \cdot 10\rho_i^2 / \Sigma_i d_i \quad (13)$$

$$L = 1 - \Sigma_i min(x_i, d_i) / \Sigma_i d_i \quad (14)$$

Experimental Procedure and Statistical Analysis

Each replication generates one demand realisation, which is then passed unchanged to the three policies, so the comparison is paired. The experiment uses the seed 42 and 100 replications for each of the three load levels, giving 900 policy-level observations. The identity of the demand realisation across policies is not assumed: the runner stores a hash of every realisation and refuses to write results unless the three policies of a replication carry the same hash and the same per-slice demand. Table 2 lists every parameter of the setup, including the parameters that a packet-level study would report and that this model does not contain.

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Table 2. Experimental setup. All values are taken from the simulation code.

Parameter	Value
Slices	4 (eMBB, URLLC, mMTC, Best Effort)
Shared bandwidth capacity	100 MHz
Shared computing capacity	100 processing units
Users per slice	Uniform integer in [20, 100]
Requests per user	Poisson distributed
Poisson rate, low / medium / high load	5.0 / 9.0 / 14.0 requests per user
Best Effort traffic multiplier	0.5
Per-request resource units	See Table 1
SLA threshold	0.90 of demanded bandwidth, identical for all four slices
QoS proxy constants	base delay 10 ms, jitter factor 0.4, offered-load cap 10
Random seed	42
Replications per load level	100
Policy-level observations	900 (3 loads x 100 replications x 3 policies)
Simulation duration, warm-up period, buffer size	Not applicable; the model is an allocation-level Monte Carlo experiment without a time or packet dimension

Because every policy is evaluated on the same demand realisations, the observations are repeated measures rather than independent samples. The primary analysis is therefore the Friedman test, reported with Kendall's coefficient of concordance as effect size, followed by paired Wilcoxon signed-rank tests for the three pairwise comparisons with Holm correction inside each load level and metric. The significance level is 0.05. The one-way analysis of variance used in the original design is retained as a supplementary check and is reported in the result files.

RESULT

Fairness of Allocation and of Demand Satisfaction

Table 3 reports the fairness measures. Equal Allocation attains an allocation index of 1.000 and a Gini coefficient of 0.000 at every load, which follows directly from the definition of the policy. Its fairness of demand satisfaction is lower and falls with load, from 0.982 at low load to 0.866 at high load, and its worst-served slice receives only 35.8% of its demand. Demand-Proportional Allocation shows the opposite pattern: its allocation index is the lowest of the three policies at every load, 0.687 at high load, yet its satisfaction index is exactly 1.000 because the policy holds every slice at a common fraction of its demand. Max-Min Fairness lies between the two, with a satisfaction index of 0.916 and the highest minimum satisfaction of the three policies at medium load, 83.2% against 49.8% for Equal Allocation. Figures 1 and 2 show the two fairness perspectives.

Table 3. Fairness of the raw allocation and of demand satisfaction, mean over 100 replications.

Load	Policy	Alloc. JFI	Alloc. Gini	Sat. JFI	Sat. Gini	Min. sat.	SLA satisfied
Low	Equal Allocation	1.000	0.000	0.982	0.043	0.794	0.860
Low	Max-Min Fairness	0.651	0.376	1.000	0.000	1.000	1.000
Low	Demand-Proportional Allocation	0.651	0.376	1.000	0.000	1.000	1.000
Medium	Equal Allocation	1.000	0.000	0.927	0.124	0.498	0.667
Medium	Max-Min Fairness	0.713	0.328	0.986	0.036	0.832	0.865
Medium	Demand-Proportional Allocation	0.660	0.369	1.000	0.000	0.901	0.580
High	Equal Allocation	1.000	0.000	0.866	0.194	0.358	0.542
High	Max-Min Fairness	0.861	0.196	0.916	0.138	0.502	0.625
High	Demand-Proportional Allocation	0.687	0.350	1.000	0.000	0.667	0.120

Alloc. = raw bandwidth allocation; Sat. = demand satisfaction; Min. sat. = satisfaction of the worst-served slice; SLA satisfied = share of slices reaching 0.90 of their demanded bandwidth.

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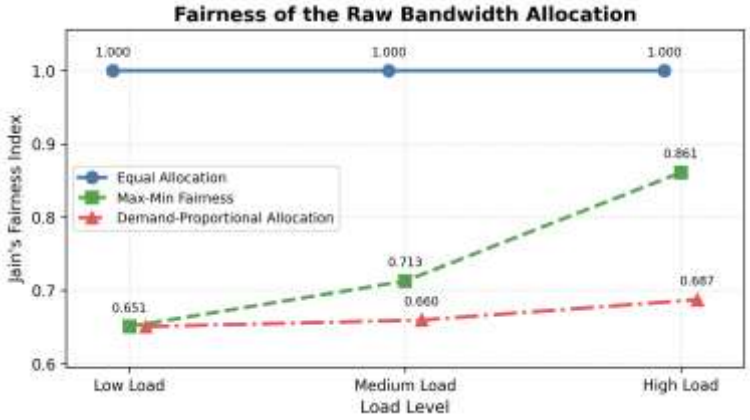


Fig. 1 Jain's fairness index of the raw bandwidth allocation.

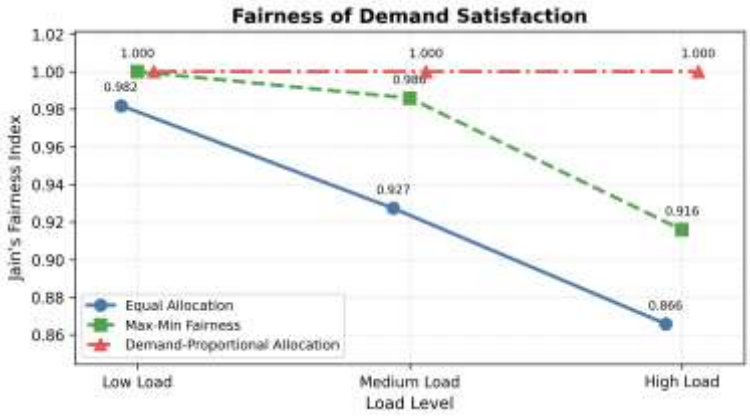


Fig. 2 Jain's fairness index of demand satisfaction.

Resource Usage and Quality-of-Service Proxies

Table 4 reports the resource and quality-of-service results. At low load the two demand-aware policies are identical, because the generated demand fits inside the shared capacity and both give every slice its full demand; each serves 57.55 MHz against 48.86 MHz for Equal Allocation, whose fixed shares leave capacity unused in some slices while starving others. At medium and high load the two demand-aware policies still carry the same load, 99.17 MHz at high load against 82.55 MHz for Equal Allocation, because both use all the capacity that the demand can absorb; they differ only in how the shortfall is distributed. Computing utilisation follows the same pattern, reaching 97.7% for the demand-aware policies and 76.4% for Equal Allocation. The delay and jitter proxies order the policies in the opposite direction to the service results: at high load Equal Allocation reaches 24.38 ms and 32.66 ms, Max-Min Fairness 18.85 ms and 18.23 ms, and Demand-Proportional Allocation the lowest values, 15.90 ms and 10.68 ms. This is a direct consequence of the proxies being demand-weighted: spreading the shortfall evenly in relative terms keeps every offered-load ratio close to the average, while a starved slice under Equal Allocation produces a large ratio. Figures 3 and 5 show served bandwidth and delay.

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Table 4. Resource usage and quality-of-service proxies, mean over 100 replications.

Load	Policy	Served BW (MHz)	BW util. (%)	CPU util. (%)	Delay (ms)	Jitter (ms)	Loss proxy (%)
Low	Equal Allocation	48.86	48.9	44.4	9.35	4.81	12.7
Low	Max-Min Fairness	57.55	57.6	48.0	10.00	4.00	0.0
Low	Demand-Proportional Allocation	57.55	57.6	48.0	10.00	4.00	0.0
Medium	Equal Allocation	68.27	68.3	65.2	16.70	15.16	32.1
Medium	Max-Min Fairness	92.05	92.1	85.0	11.62	5.75	9.9
Medium	Demand-Proportional Allocation	92.05	92.1	85.0	11.28	5.18	9.9
High	Equal Allocation	82.55	82.6	76.4	24.38	32.66	44.6
High	Max-Min Fairness	99.17	99.2	97.7	18.85	18.23	33.3
High	Demand-Proportional Allocation	99.17	99.2	97.7	15.90	10.68	33.3

Delay, jitter and the loss proxy are analytical functions of the demand-to-allocation ratio, not packet-level measurements.

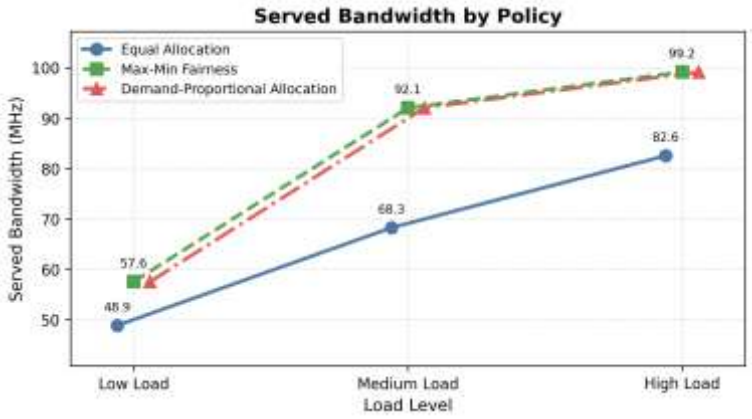


Fig. 3 Mean served bandwidth, used as a resource-level throughput proxy.

Service-Level Satisfaction

The service results separate the policies most clearly, as Figure 4 shows. At low load the two demand-aware policies satisfy every slice, while Equal Allocation satisfies 86.0% of them. At medium load Max-Min Fairness satisfies 86.5%, Equal Allocation 66.8% and Demand-Proportional Allocation 58.0%. At high load the gap widens: Max-Min Fairness satisfies 62.5%, Equal Allocation 54.2% and Demand-Proportional Allocation only 12.0%. The last figure is not a contradiction of its perfect satisfaction fairness but a consequence of it: when the common satisfaction ratio falls below the threshold, all four slices fail together. Figure 6 places the two properties side by side and shows that no policy occupies the upper right corner, where high satisfaction fairness would coincide with the highest carried load and the highest service compliance.



Fig. 4 Mean share of slices meeting the 0.90 service level agreement threshold.

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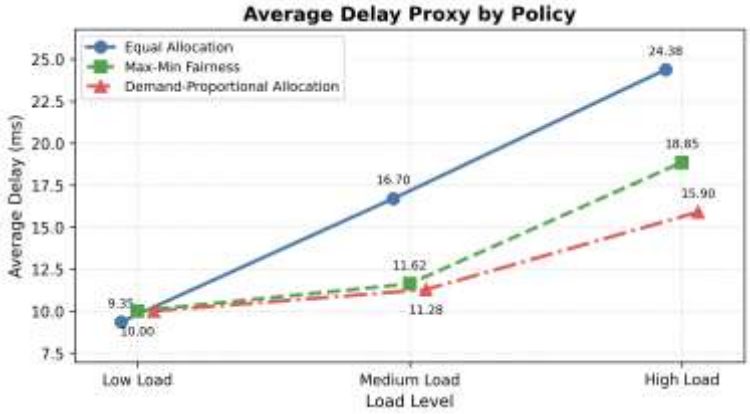


Fig. 5 Mean delay proxy by policy and load level.

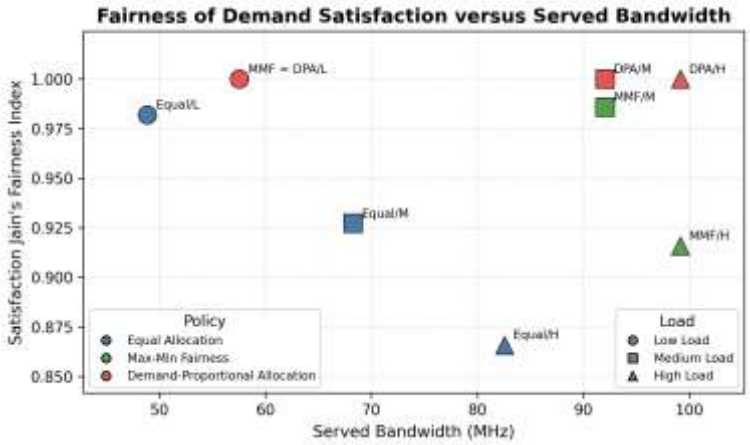


Fig. 6 Fairness of demand satisfaction against served bandwidth; each point is one policy at one load level.

Statistical Validation

Table 5 reports the paired analysis for four representative metrics. The Friedman test rejects the hypothesis of equal policies for almost every combination of load and metric; the strongest effect is satisfaction fairness at high load, with a Kendall coefficient of 0.973. The Holm-corrected Wilcoxon tests confirm the pattern seen in the means: Equal Allocation differs from both demand-aware policies everywhere, while Max-Min Fairness and Demand-Proportional Allocation are indistinguishable at low load, where they produce numerically identical allocations, and differ significantly at medium and high load for satisfaction fairness, delay and service compliance. Served bandwidth is the one metric on which the two demand-aware policies never differ, since both absorb all the capacity the demand can use.

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Table 5. Paired statistical analysis. Friedman test with Kendall's W, and Holm-corrected p values of the paired Wilcoxon signed-rank tests.

Load	Metric	Chi-square	p	W	Equal vs MMF	Equal vs DPA	MMF vs DPA
Low	Satisfaction Jain's Fairness Index	126.0	< 0.001	0.630	< 0.001	< 0.001	identical
Low	Served Bandwidth (MHz)	126.0	< 0.001	0.630	< 0.001	< 0.001	identical
Low	Average Delay (ms)	11.5	0.003	0.058	0.183	0.183	identical
Low	SLA Satisfaction Rate	112.0	< 0.001	0.560	< 0.001	< 0.001	identical
Medium	Satisfaction Jain's Fairness Index	177.1	< 0.001	0.885	< 0.001	< 0.001	< 0.001
Medium	Served Bandwidth (MHz)	187.4	< 0.001	0.937	< 0.001	< 0.001	identical
Medium	Average Delay (ms)	119.9	< 0.001	0.599	< 0.001	< 0.001	< 0.001
Medium	SLA Satisfaction Rate	59.9	< 0.001	0.300	< 0.001	0.006	< 0.001
High	Satisfaction Jain's Fairness Index	194.7	< 0.001	0.973	< 0.001	< 0.001	< 0.001
High	Served Bandwidth (MHz)	192.1	< 0.001	0.961	< 0.001	< 0.001	identical
High	Average Delay (ms)	176.9	< 0.001	0.885	< 0.001	< 0.001	< 0.001
High	SLA Satisfaction Rate	132.9	< 0.001	0.664	< 0.001	< 0.001	< 0.001

"identical" marks a pair whose per-replication values are equal in every replication, so no test is applicable. The full analysis of all eleven metrics is provided in the result files.

One case deserves comment because it shows why the paired analysis matters. For the jitter proxy at low load the Friedman test finds no difference at all (chi-square 0.0, p = 1.000): Equal Allocation produces a lower value than the demand-aware policies in exactly half of the replications and a higher value in the other half, so the mean ranks coincide. The one-way analysis of variance on the same data reports a significant difference (F = 6.32, p = 0.002) because the means differ. The paired test describes the per-replication behaviour more faithfully. The delay proxy at low load behaves similarly: the omnibus test is significant (p = 0.003) while the pairwise signed-rank test between Equal Allocation and Max-Min Fairness is not (p = 0.183).

Sensitivity Analysis

The comparison was repeated over a range of shared capacities, using the same three policies, the same seed and the same demand realisations, in order to test how far the ranking depends on the chosen operating point. Table 6 reports the outcome at high load. The qualitative picture is stable across the whole range: Equal Allocation keeps a perfect allocation index, Demand-Proportional Allocation keeps a perfect satisfaction index, and Max-Min Fairness satisfies the largest number of service commitments at every capacity. The size of the gap, however, depends strongly on scarcity. When the capacity is reduced to 60 MHz the service compliance of Demand-Proportional Allocation collapses to 0.0%, while at 140 MHz it recovers to 49.0% and the three policies converge. Varying the service threshold instead of the capacity gives the same message: relaxing it from 0.90 to 0.70 raises the compliance of Demand-Proportional Allocation from 12.0% to 38.0%, whereas Max-Min Fairness moves only from 62.5% to 70.5%. The conclusions of this study are therefore statements about how the policies respond to scarcity, not universal rankings.

Table 6. Sensitivity of the comparison to the shared bandwidth capacity at high load, same three policies and same demand realisations.

Capacity (MHz)	Sat. JFI Equal	Sat. JFI MMF	Sat. JFI DPA	SLA Equal	SLA MMF	SLA DPA
60	0.787	0.807	1.000	0.245	0.268	0.000
80	0.831	0.864	1.000	0.388	0.458	0.030
100	0.866	0.916	1.000	0.542	0.625	0.120
120	0.896	0.956	1.000	0.603	0.713	0.290
140	0.920	0.978	1.000	0.627	0.812	0.490

DISCUSSION

The three policies do not disagree about which allocation is best; they disagree about what should be equalised. Equal Allocation equalises quantities, and its perfect allocation index is a restatement of that choice rather than an empirical finding. Demand-Proportional Allocation equalises the fraction of demand that is served, which is why its satisfaction index is exactly one whenever the capacity binds. Max-Min Fairness equalises the allocation of the slices that remain unsatisfied after the small demands have been met, which is why it protects the worst-served

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slice and, in this model, satisfies the largest number of service commitments. Each policy is optimal for its own criterion, so no policy can be declared the fairest without first naming the criterion.

This is the substance of the objection to reporting fairness on raw allocations alone. In the present results the two perspectives order the policies in opposite directions at every load level: Equal Allocation is first on allocation fairness and last on satisfaction fairness, while Demand-Proportional Allocation is last on the first measure and first on the second. Neither ordering predicts service compliance, where Max-Min Fairness leads. The observation is consistent with work that ties allocation to service commitments rather than to equality (Zhang et al., 2022; Li et al., 2024) and with equitable sharing schemes that introduce explicit priorities or minimum guarantees (Yarkina et al., 2022; Bamdad et al., 2026). It also matches the testbed finding that equal resource assignments do not produce equal application performance (Moreira et al., 2024).

The trade-offs are visible in the other metrics as well. Equal Allocation leaves capacity unused whenever a slice demands less than its fixed share, so it carries the least traffic at every load and produces the largest delay and jitter proxies at high load. The two demand-aware policies carry the same load, which shows that the difference between them concerns the distribution of the shortfall and not the efficiency of the allocation. Demand-Proportional Allocation obtains the most favourable delay and jitter proxies because those proxies are demand-weighted averages of the offered-load ratio, and holding every slice at the same ratio minimises such an average; the same uniformity makes all four slices fail the service threshold simultaneously. This explains the apparent paradox between its perfect satisfaction fairness and its low service compliance, and it argues for reporting an aggregate quality-of-service average together with a per-slice service criterion rather than in place of it (Rajahrajasingh et al., 2026).

Relative to the wider literature, the contribution here is methodological. Sophisticated allocation mechanisms based on optimisation, control theory or learning are usually compared against these very policies (Ma et al., 2022; Chai & Wang, 2025; Fryganiotis et al., 2025; Chakraborty & Sivalingam, 2023), and the value of such a comparison depends on the baselines being characterised carefully and evaluated under identical conditions. The present study supplies that characterisation for the three policies: it fixes the demand realisation across policies, reports fairness from three perspectives, states the analytical nature of the quality-of-service proxies, applies statistical tests appropriate for a paired design, and shows that the three rules are instances of one weighted proportional-fair program. The last point also settles the terminology question: proportional-to-demand sharing is proportional fairness only in the weighted sense, with the demands acting as weights (Kelly et al., 1998).

Limitations

The study evaluates an analytical, allocation-level model. There is no packet generation, no queue, no buffer and no radio protocol stack, so delay, jitter and loss are proxies derived from the demand-to-allocation ratio and must not be read as measurements from a physical or packet-level testbed. The demand is synthetic: user counts are uniform and request counts are Poisson, which reproduces neither burstiness nor temporal correlation, and the model has no time dimension, so no conclusion can be drawn about dynamic load transitions or about reconfiguration cost. The shared capacities are normalised values rather than measurements from a deployment. A single service threshold is applied to all four slices, so differentiated per-slice commitments and priority weights are outside the scope of these results; the sensitivity analysis varies capacity and threshold but not the number or the profile of the slices, because additional slice profiles would not come from the original model. Finally, the study compares three deterministic policies and proposes none, so its findings describe those policies and not allocation in general.

CONCLUSION

This paper reported a controlled comparison of Equal Allocation, Max-Min Fairness and Demand-Proportional Allocation for four 5G network slices under low, medium and high stochastic demand, using 100 paired replications per load level in which the three policies received identical demand realisations. The comparison shows that the three policies win on three different criteria. Equal Allocation attains an allocation fairness index of 1.000 at every load but its satisfaction fairness falls to 0.866 at high load, it carries the least traffic (82.55 MHz) and it produces the largest delay proxy (24.38 ms). Demand-Proportional Allocation attains perfect satisfaction fairness (1.000) and the smallest delay proxy (15.90 ms) but satisfies only 12.0% of the service commitments at high load. Max-Min Fairness satisfies 62.5% of them while carrying the same 99.17 MHz as the proportional rule, which makes it the most balanced of the three in this model. The paired tests confirm that these differences are systematic rather than sampling artefacts, and the sensitivity analysis shows that the ordering persists across capacities from 60 to 140 MHz while the size of the gaps shrinks as scarcity is relieved.

The practical answer to the research question is that a fairness index computed on raw allocations should not be used on its own to justify an allocation policy for network slicing. Reporting equality of resources, fairness of demand satisfaction and the share of slices meeting their service commitment together costs nothing and prevents the three from being confused. Future work should extend the benchmark with per-slice service thresholds and

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priority weights, with a queueing or packet-level model that would replace the analytical proxies, and with dynamic load transitions, so that the same controlled design can be applied to policies that adapt over time.

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